APPLICATION

FOR

UNITED STATES LETTERS PATENT

TITLE: INTERFERENCE REDUCTION BY STEP FUNCTION REMOVAL

APPLICANT: STUART A. GOLDEN AND NAIEL K. ASKAR

CERTIFICATE OF MAILING BY EXPRESS MAIL

Express Mail Label No. EL870691653US

I hereby certify that this correspondence is being deposited with the United States Postal Service as Express Mail Post Office to Addressee with sufficient postage on the date indicated below and is addressed to the Commissioner for Patents, Washington, D.C. 20231.

December 28, 2001
Date of Deposit

Signature

Gabe Lewis
Typed or Printed Name of Person Signing Certificate

INTERFERENCE REDUCTION BY STEP FUNCTION REMOVAL

TECHNICAL FIELD

This invention relates to reception of a signal.

BACKGROUND

A received signal may include a desired signal from a desired source along with one or more undesired signals, such as, for example, a noise signal (e.g., additive noise such as white Gaussian noise) from a noise source, and/or an interfering signal from an interfering source (e.g., main-lobe or side-lobe energy of the interfering signal). The received signal also may include an offset component such as, for example, a DC (direct current) offset component, that may be undesirable. The offset component is an additional additive term and may be a constant offset such as, for example, a DC offset, or may be a non-constant offset such as, for example, a step function.

To extract the desired signal from the received signal, characteristic parameters (e.g., data bits, frequency offset, DC offset) that model the received signal may be estimated. It may be desirable to perform preprocessing of the received signal prior to estimating the characteristic parameters, such

as, for example, estimating the offset and removing its effect. For example, the offset may be estimated as a mean of the received signal and the mean may then be subtracted from the received signal.

The offset of the received signal may vary, for example, because of variation in the interfering signal. Such variations may cause the mean of the received signal to provide a poor estimate of the signal offset. Subtracting a poor estimate of the offset would then bias the estimates of the characteristic parameters and lead to inaccurate results.

DESCRIPTION OF DRAWINGS

Fig. 1 is a schematic diagram of a communication system configured to estimate and correct a signal having an offset that may be modeled as a step function.

Fig. 2 is a diagram illustrating two time-division, multiple-access (TDMA) users that are not aligned in time and that may cause interference which may appear as an additional signal offset in the form of a step function.

Fig. 3 is a schematic diagram of a receiver that may be used with the communication system of Fig. 1.

Fig. 4 is a diagram illustrating a step function that may be used to model the signal offset of the system of Fig. 1.

Fig. 5 is a schematic flow diagram illustrating a systematic process for offset correcting a signal having an offset that may be modeled as a step function by removing the step function of Fig. 4 from the received signal.

Like reference symbols in the various drawings indicate like elements.

DETAILED DESCRIPTION

For illustrative purposes, a process is described for interference reduction by offset correcting a signal, where the offset may be modeled as including a step function and the signal is corrected by removing the undesired step function. For clarity of exposition, the description generally proceeds from an account of general elements and their high level relationship to a detailed account of illustrative roles, configurations, and components of the elements.

Referring to Fig. 1, a generalized system 100 (e.g., a global system for mobile communications (GSM), a time-division, multiple-access (TDMA) system, or a frequency-division, multiple access (FDMA) system) may be used to receive a transmitted signal and to correct the offset of the received signal, where the signal offset may be modeled as including a step function. Exemplary components of the system 100 are described in greater detail below.

The system 100 of Fig. 1 generally includes a transmitter 110, a receiver 130 (e.g., a superheterodyne receiver, a dual-conversion superheterodyne receiver, or a direct conversion receiver), and a channel 150 that models how the environment has changed the transmitted signal as perceived at the input port of the receiver.

In general, the transmitter 110 and the receiver 130 may include any devices, systems, pieces of code, and/or combinations of these that may be used to transmit or receive, respectively, a waveform z(t) that generally may be represented as

$$z(t) = \mathrm{Re}\{s(t)\}\cos(\omega_0 t) - \mathrm{Im}\{s(t)\}\sin(\omega_0 t)\ . \qquad (1.0)$$

In equation (1.0), $s(t)$ may denote a complex signal, $\omega_0 = 2\pi f_0$ may be an associated carrier frequency, and $\mathrm{Re}\{s(t)\}$ and $\mathrm{Im}\{s(t)\}$ denote respectively, real and imaginary parts of s(t).

A transmitter (e.g., transmitter 110) and/or a receiver (e.g., receiver 130) generally may include, for example, a mixer (e.g., mixer 135), a summer, a phase locked loop, a frequency synthesizer, a filter (e.g., filter 137), an oscillator (e.g., local oscillator 133), a frequency divider, a phase modulator, a down converter, an amplifier, a phase shifter, an analog-to-digital (A/D) converter or a digital-to-analog (D/A) converter (e.g., A/D converter 137), a

microprocessor (MPU), a digital signal processor (DSP), a computer, or a signal processing circuit, whether linear or nonlinear, analog or digital, and/or any combination of these elements.

More specifically, receiver 130 may include a down-converter for down-converting an input signal from radio frequency (RF) to baseband. The down-converter includes the local oscillator 133, the mixer 135, and the filter 137 (e.g., an infinite impulse response filter, a finite impulse response filter). The receiver 130 also may include an A/D converter to generate a discrete signal from a continuous input and, for performing step parameter estimation and offset correction, any device, system, or piece of code suitable for that task, such as, for example, step parameter estimator and signal offset corrector 139. The step parameter estimator and signal offset corrector 139 may include, for example, a microprocessor control unit (MCU), a digital signal processing (DSP) component, a computer, a piece of code, a signal processing circuit, whether linear or nonlinear, analog or digital, and/or any combination of these for use in performing the step parameter estimation and/or the offset correction, including step function removal.

The transmitter 110 transmits a signal $z(t)$ over the channel 150. The channel 150 may include any medium over

which a signal may be communicated, such as, for example, an RF (radio frequency) portion of the electromagnetic spectrum, and or any other portion of the electromagnetic spectrum. Associated with the channel are an interference source 151 that generates an interference signal $I(t)$ and a noise source 153 that generates a noise signal $w(t)$. The noise source 153 and the interference source 151 add noise $w(t)$ and interference $I(t)$, respectively, to $z(t)$ to form a signal $r(t)$ received by the receiver.

The noise $w(t)$ may include, for example, additive white Gaussian noise that may have a zero or non-zero mean, while the interfering signal $I(t)$ may have very different characteristics before and after an event that occurs within the burst. For example, if the interfering source is due to a different TDMA user who is transmitting at the same frequency as, but not time aligned with, the desired user, then the interference may appear as being turned on and off during the burst for multiple bursts.

Fig. 2 illustrates one example of burst interference that may generate a signal offset that may be represented as including a step function at the input of the data bit estimator 140. The data bit estimator 140 may include, for example, a matched filter, and/or a decoder such as, for example, a convolution decoder, and may perform functions

including de-interleaving or decoding, and further may provide an estimate of data bits sent over the channel 150.

Note that the signals $z(t)$ and $I(t)$, as shown in Fig. 2, are illustrative only and may not represent certain characteristics of actual physical signals. As shown, signal $z(t)$ is transmitted in time slot n of a first TDMA waveform 210, while the interference signal $I(t)$ is transmitted in time slot m of a second TDMA waveform 220. Each TDMA waveform is associated with different TDMA channels (e.g., different GSM base stations with or without different hopping patterns).

The time slots for these first and second TDMA waveforms are not time aligned with each other (e.g., each time slot of the second TDMA waveform lags (or leads) the corresponding time slot of the first TDMA channel by the same time increment of t_2-t_1). The interference signal $I(t)$ also may have a power that is much greater than that of $z(t)$ and a center frequency different than the center frequency ω_0 of $z(t)$, such as, for example, a center frequency that approximates a harmonic of ω_0.

Because of the phase difference between the two TDMA waveforms, the transmission of signal $I(t)$ at time t_2 may appear as interference that is turned on and off and is included in signal $z(t)$. Moreover, a TDMA channel structure, such as, for example, a TDMA time-slot assignment methodology,

may ensure that $z(t)$ and $I(t)$ transmit in lockstep, causing $z(t)$ to experience burst interference from $I(t)$ beginning at the same relative point in each time-slot in which $z(t)$ is transmitted (e.g., t_2-t_1 from the beginning of each time slot).

Referring again to Fig. 1, the receiver 130 receives from the channel a signal $r(t)$ that includes $z(t) + I(t) + w(t)$. A mixer 135 produces $y(t)$ by mixing $r(t)$ with the combination of a sinusoidal signal $\Omega(t)$ generated by local oscillator 133 with an attenuated version of $r(t)$ that may leak into the local oscillator 133. The leakage of $r(t)$ into the local oscillator 133 is represented by multiplying the received signal $r(t)$ by an attenuation factor γ to produce $\gamma r(t)$, and then summing $\gamma r(t)$ with the output $\Omega(t)$ of an ideal local oscillator 134. Leakage of $r(t)$ into the local oscillator 133 causes $y(t)$ to include the signal mix of $r(t)[\Omega(t) + \gamma r(t)]$.

Thereafter, $y(t)$ passes through a low pass or band pass filter and/or an A/D (analog-to-digital) converter 137 (e.g., an integrator that performs the functions of A/D conversion and low pass filtering) to produce a discrete signal y_n that may include an undesirable offset component. Thereafter, y_n is processed further by step parameter estimator and offset corrector 139, which models the offset as a step function and estimates parameters descriptive of the step function. The offset of y_n is corrected by offset corrector 139 based on the

estimated step function parameters.

Fig. 3 illustrates a receiver 130 that may be used to implement the system of Fig. 1, and in which a signal $r(t)$ leaks into an ideal local oscillator 334. The signal $r(t)$ may include a transmitted signal $z(t)$, a sum of interfering signals $I(t)$, and additive white Gaussian noise signal $w(t)$. Signal $z(t)$ may be represented as a real signal resulting from upconversion of a complex signal $s(t)$:

$$z(t)=\mathrm{Re}\{s(t)\}\cos\omega_0 t-\mathrm{Im}\{s(t)\}\sin\omega_0 t. \tag{1.1}$$

Due to the leakage of $r(t)$ into the local oscillator 333, the mixer 335 may not simply multiply $r(t)$ by a sinusoid (e.g., $A_0 e^{-j\omega_0 t}$, where A_0 is a known value). Instead $r(t)$ is multiplied by the sinusoid and an attenuated version of the input, $\gamma r(t)$. The resulting signal may be expressed as:

$$\begin{aligned} y(t) = A_0[z(t)+I(t)+w(t)]e^{-j\omega_0 t} + \gamma I^2(t) + \gamma z^2(t) + \gamma w^2(t) + \\ 2\gamma z(t)I(t) + 2\gamma z(t)w(t) + 2\gamma w(t)I(t). \end{aligned} \tag{1.2}$$

Substituting equation 1.1 for $z(t)$ produces

$$\begin{aligned} y(t) &= A_0[\mathrm{Re}\{s(t)\}\cos\omega_0 t - \mathrm{Im}\{s(t)\}\sin\omega_0 t]e^{-j\omega_0 t} \\ &+ A_0 I(t)e^{-j\omega_0 t} + A_0 w(t)e^{-j\omega_0 t} + \gamma I^2(t) \\ &+ \gamma[\mathrm{Re}\{s(t)\}\cos\omega_0 t - \mathrm{Im}\{s(t)\}\sin\omega_0 t]^2 + \gamma w^2(t) \\ &+ 2\gamma[\mathrm{Re}\{s(t)\}\cos\omega_0 t - \mathrm{Im}\{s(t)\}\sin\omega_0 t]I(t) \\ &+ 2\gamma[\mathrm{Re}\{s(t)\}\cos\omega_0 t - \mathrm{Im}\{s(t)\}\sin\omega_0 t]w(t) + 2\gamma w(t)I(t). \end{aligned} \tag{1.3}$$

If the attenuation term γ is sufficiently small compared to the signal amplitude, then $y(t)$ may be approximated as

$$y(t) \approx A_0\left[\mathrm{Re}\{s(t)\}\cos\omega_0 t - \mathrm{Im}\{s(t)\}\sin\omega_0 t\right]e^{-j\omega_0 t} + A_0 I(t)e^{-j\omega_0 t} + A_0 w(t)e^{-j\omega_0 t} + \gamma I^2(t), \tag{1.4}$$

in which the term $\gamma I^2(t)$ is retained because it is assumed that $I(t)$ is of substantially greater power than $z(t)$.

The signal $y(t)$ then passes through a low pass filter 339, for example, to produce $y_{low}(t)$, where $y_{low}(t)$ may be approximated as:

$$y_{low}(t) \approx \frac{A_0}{2}s(t) + \gamma I_{bb}^2(t) + w_{bb}(t)\,, \tag{1.5}$$

in which the term $A_0 I(t)e^{-j\omega_0 t}$ is assumed to be substantially removed by the low pass filter and, therefore, has been dropped. In equation (1.5), the term $w_{bb}(t)$ represents a baseband portion of $A_0 w(t)e^{-j\omega_0 t}$ that remains after passage through the low pass filter 339. Assuming $I(t)$ to be generally sinusoidal, $\gamma I^2(t)$ may include an offset component (e.g., a DC offset) and a bandpass component at twice the center frequency of $I(t)$. The low pass filter may substantially remove the bandpass component of $\gamma I^2(t)$ while leaving essentially unaffected the offset component, represented in equation (1.5) as γI_{bb}^2. When for example, $I(t)$ is switched on or off, the offset component of γI_{bb}^2 may be modeled as a step function.

An A/D converter 341 may be used to generate a discrete signal y_n based on the signal $y_{low}(t)$. Assuming that γI_{bb}^2 may be represented as a step function, the discrete signal y_n may be represented as:

$$y_n \approx \frac{A_0}{2} s_n(\theta) + c1 + (c2 - c1)u_{n-\alpha} + w_n \quad (1.6)$$

where $s_n(\theta)$ is a discrete model of the baseband signal, θ is a vector of unknown signal parameters (e.g., data bits, frequency offset), and w_n is a discrete representation of zero-mean additive white Gaussian noise remaining after passing $w(t)$ through the low pass filter 339 and the A/D converter 341. Also, referring now to Fig. 4, u_n represents a unit step function that transitions from zero to one at n equals zero, such that $c1 + (c2 - c1)u_{n-\alpha}$ represents a step function with amplitude of $c1$ before the step transition and amplitude of $c2$ after the step transition, where the step transition occurs at time n equals α.

Referring again to Fig. 3, the signal y_n is provided to the parameter estimator and offset corrector 139. The parameters $c1$, $c2$ and α of the step function are estimated, and the estimated parameters then are used to correct the offset of signal y_n, to produce an output signal that may be represented as:

$$\frac{A_0}{2} s_n(\theta) + w_n \; . \quad (1.7)$$

The parameter estimator 139 may estimate the step function parameters based on, for example, gradient descent algorithms (e.g., the least-mean-square algorithm, Newton's method, the

steepest descent method, and/or any combination of these methods) and/or the maximum-likelihood (ML) method.

The ML method provides a general method of maximizing the likelihood of the joint probability density function of the values of the received signal vector ($y_0, \ldots, y_{N-1}$) given an intended signal vector ($x_0, \ldots, x_{N-1}$). For the case when the observations are independent, a combined probability, or likelihood function, may be expressed as the product of the probability densities of the independent received signal vector samples, i.e., $p = p(y_0)\ldots p(y_{N-1})$, where it may be assumed that each probability density can be modeled as a Gaussian density. The likelihood function p is then maximized to find the optimal parameters using any suitable optimization technique (e.g., a non-linear optimization technique), such as, for example, the Nelder-Mead method (a method based upon the simplex algorithm), the steepest descent method, the LMS (least-mean-square) method, the Levenberg-Marquardt method (a least squares approach), the Davidson-Fletcher-Powell method (a quasi-Newton based method), or the Broyden-Fletcher-Goldfarb-Shannon method (a quasi-Newton based method), and/or any combination of one or more of these or other optimization methods.

More specifically, a ML estimate of the step function parameters $c1$, $c2$, and α can be obtained from the samples y_n as described above. For example, we may take the baseband signal

model $s_n(\theta)$ and noise model w(n) to have a zero mean, since their means can be incorporated into the step function parameters. Using $\frac{A_0}{2}s_n(\theta)+c1+(c2-c1)u_{n-\alpha}$ as an expression of the mean of the individual values of the received signal vector produces the following ML likelihood function of the complex observation:

$$p=\prod_{n=0}^{N-1}\frac{1}{\sqrt{\pi}\sigma}e^{-\left|y_n-\frac{A_0}{2}s_n(\theta)+c1+(c2-c1)u_{n-\alpha}\right|^2/\sigma^2}, \tag{1.8}$$

which may be simplified to

$$p=\left(\frac{1}{\sqrt{\pi}\sigma}\right)^N e^{-\frac{1}{\sigma^2}\sum_{n=0}^{N-1}\left|y_n-\frac{A_0}{2}s_n(\theta)+c1+(c2-c1)u_{n-\alpha}\right|^2}. \tag{1.9}$$

To maximize the value of *p*, it is sufficient to minimize the value of

$$f=\sum_{n=0}^{N-1}\left|y_n-\frac{A_0}{2}s_n(\theta)-c1-(c2-c1)u_{n-\alpha}\right|^2, \tag{1.10}$$

which is a nonlinear least squares optimization problem. Specifically, the unknown parameters in equation (1.6) can be determined by solving

$$\min_{\theta,c1,c2,\alpha} f=\sum_{n=0}^{N-1}\left|y_n-\frac{A_0}{2}s_n(\theta)-c1-(c2-c1)u_{n-\alpha}\right|^2. \tag{1.11}$$

To determine the solution of (1.11), it is useful to partition equation (1.11) over a first interval before the transition of the square wave and a second interval after the transition of the square wave. That is, equation (1.11)

becomes:

$$f = \sum_{n=0}^{\alpha-1} \left| y_n - \frac{A_0}{2} s_n(\theta) - c1 \right|^2 + \sum_{n=\alpha}^{N-1} \left| y_n - \frac{A_0}{2} s_n(\theta) - c2 \right|^2 . \tag{1.12}$$

Equation (1.12) may be minimized over (θ, $c1$, $c2$, α) jointly using any of the previously mentioned optimization methods. However, since $c1$ and $c2$ are in separate terms of the objective function, their estimates also may be solved for separately. For example, the estimate for $c1$ may be obtained analytically by differentiating the portion of equation (1.12) that corresponds to the first interval with respect to $c1$, setting the result equal to zero, and solving for $c1$. The estimate of $c2$ may be solved by operating upon the portion of equation (1.12) that corresponds to the second interval in like fashion.

The estimates of $c1$ and $c2$ also may be obtained qualitatively. For example, the estimate for $c1$ may be expressed as a mean of an error between the observation y_n and the signal prediction $s_n(\theta)$ before the square wave transitions; similarly, the estimate for $c2$ may be expressed as a mean of an error between the observation y_n and the signal prediction $s_n(\theta)$ after the square wave transitions. Hence, the estimates $\hat{c}1$ of $c1$ and $\hat{c}2$ of $c2$ may be expressed as

$$\hat{c}1 = \frac{1}{\alpha} \sum_{n=0}^{\alpha-1} \left[y_n - \frac{A_0}{2} s_n(\theta) \right] \tag{1.13}$$

and

$$\hat{c}2 = \frac{1}{N-a}\sum_{n=\alpha}^{N-1}\left[y_n - \frac{A_0}{2}s_n(\theta)\right]. \tag{1.14}$$

Equations (1.13) and (1.14) then may be substituted back into the objective function of equation (1.12), resulting in the following expression of the objective function:

$$\begin{aligned} f &= \sum_{n=0}^{\alpha-1}\left|y_n - \frac{1}{\alpha}\sum_{m=0}^{\alpha-1}y_m - \frac{A_0}{2}s_m(\theta) + \frac{1}{\alpha}\sum_{m=0}^{\alpha-1}\frac{A_0}{2}s_m(\theta)\right|^2 \\ &+ \sum_{n=\alpha}^{N-1}\left|y_n - \frac{1}{N-\alpha}\sum_{m=\alpha}^{N-\alpha}y_m - \frac{A_0}{2}s_n(\theta) + \frac{1}{N-\alpha}\sum_{m=\alpha}^{N-\alpha}\frac{A_0}{2}s_m(\theta)\right|^2. \end{aligned} \tag{1.15}$$

Now, equation (1.15) is a function of the observation, y_n, the unknown signal parameters, θ, and the location of the step function, α. All of these parameters may be jointly estimated, for example, using non-linear optimization techniques as described above.

Nevertheless, it also may be possible to estimate only the unknown parameters $c1$, $c2$ and α based on expanding and rearranging the terms of equation (1.15) to give

$$\begin{aligned} f &= \sum_{n=0}^{N-1}\left|y_n - \frac{A_0}{2}s_n(\theta)\right|^2 - g(\alpha) \\ &- \alpha\left|\frac{1}{\alpha}\sum_{n=0}^{\alpha}\frac{A_0}{2}s_n(\theta)\right|^2 - (N-\alpha)\left|\frac{1}{N-\alpha}\sum_{n=\alpha}^{N-\alpha}\frac{A_0}{2}s_n(\theta)\right|^2 \\ &+ 2\alpha\,\mathrm{Re}\left[\frac{1}{\alpha}\sum_{m=0}^{\alpha}y_m\right]^*\left[\frac{1}{\alpha}\sum_{m=0}^{\alpha}\frac{A_0}{2}s_m(\theta)\right] \\ &+ 2(N-\alpha)\,\mathrm{Re}\left[\frac{1}{N-\alpha}\sum_{m=\alpha}^{N-\alpha}y_m^*\right]\left[\frac{1}{N-\alpha}\sum_{m=\alpha}^{N-\alpha}\frac{A_0}{2}s_m(\theta)\right], \end{aligned} \tag{1.16}$$

where

$$g(\alpha) = \alpha\left|\frac{1}{\alpha}\sum_{n=0}^{\alpha} y_n\right|^2 + (N-\alpha)\left|\frac{1}{N-\alpha}\sum_{n=\alpha}^{N-\alpha} y_n\right|^2. \qquad (1.17)$$

The first term in equation (1.16) is an expression of mean square error between the observation y_n and the signal prediction $\frac{A_0}{2}s_n(\theta)$, while the second term is explicitly provided by equation (1.17).

All of the other terms of equation (1.16) involve averages of the signal prediction $\frac{A_0}{2}s_n(\theta)$ and may be approximated as zero if the expectation of $s_n(\theta)$ is approximately equal to zero, for both before and after the transition of the step function. When the expectation of $s_n(\theta)$ may not be approximated as zero, the parameters may be estimated using a method that retains these terms. For example, the parameters may be estimated by starting with a seed value of α that may be used to determine an estimate of θ, which, in turn, may be used to produce an estimate of α. The method may be iterative and may continue to alternate between estimating α and θ until convergence to a desired degree of precision is achieved.

Nevertheless, for many signals, such as, for example, a GSM signal for which the expected value of the underlying binary

data stream is zero or approximately zero, it is reasonable to assume that the average of the signal prediction $s_n(\theta)$ is equal or approximately equal to zero when taken over a sufficiently large interval. For example, the signal prediction may be expressed as:

$$s_n(\theta) = \sum_{k=0}^{L} j^k d_k h_{n-k} \ , \tag{1.18}$$

where d_k is an original binary data sequence with an expectation of zero, and h_n is the combined action of the transmit filter, the channel filter, and the receive filter. Here the vector of unknown parameters, θ, can be taken as the complete data sequence d_k for all k and the complete filter h_n for all n. Because the expectation of the binary sequence is zero and the binary sequence is independent of the combined filter, then the expectation of the signal in equation (1.18) is zero. That is,

$$E\{d_k\} = 0 \text{ implies } E\{s_n(\theta)\} = 0 \,. \tag{1.19}$$

Hence, approximating as zero the expectation of $s_n(\theta)$, the objective function of (1.16) becomes:

$$f \approx \sum_{n=0}^{N-1} \left| y_n - \frac{A_0}{2} s_n(\theta) \right|^2 - g(\alpha) \ , \tag{1.20}$$

and equation (1.20) may be minimized by selecting an α that maximizes $g(\alpha)$. That is,

$$\hat{\alpha} \approx \arg\max_{\alpha} g(\alpha) = \arg\max_{\alpha} \alpha \left| \frac{1}{\alpha} \sum_{n=0}^{\alpha} y_n \right|^2 + (N-\alpha) \left| \frac{1}{N-\alpha} \sum_{n=\alpha}^{N-\alpha} y_n \right|^2 . \tag{1.21}$$

Fig. 5 illustrates a method 139 for optimizing equation (1.21) that may be used to implement the system of Fig. 1. A sum of the received data is computed and stored (step 510), where the sum may be expressed as:

$$Y_s = \sum_{n=0}^{N-1} y_n \, . \tag{1.22}$$

Next, temporary parameters Y_{ps} (a partial sum of the data) and g_{max} are set initially to zero, and temporary parameter α_{Test} is set initially equal to one (step 520).

Using the parameters of step 520, estimates g_{max}, $\hat{\alpha}$, and $\hat{Y}_{ps}$ may be computed iteratively over increasing values of α_{Test} while α_{Test} is less than or equal to N-1, the number of data samples (steps 530). For example, as shown in Fig. 5, estimating g_{max}, $\hat{\alpha}$, and $\hat{Y}_{ps}$ may include adding the current data $Y_{\alpha_{Test-1}}$ to the partial sum of the data Y_{ps} to generate an updated partial sum Y_{ps} (step 533). An updated value for the object function g then may be determined as:

$$g = \frac{1}{\alpha_{Test}} \left| Y_{ps} \right|^2 + \frac{1}{N - \alpha_{Test}} \left| Y_s - Y_{ps} \right|^2 \tag{1.23}$$

(step 535). The updated value of g then may be compared to the stored value of g_{max} (step 537), and if updated g is greater than g_{max}, then g_{max} may be set equal to updated g as a best current guess of the maximum of g, $\hat{\alpha}$ may be set equal to α_{Test}, and $\hat{Y}_{ps}$ may be set equal to Y_{ps} (step 539). After updating the values of

g_{max}, $\hat{\alpha}$, and $\hat{Y}_{ps}$ (step 539), α_{Test} may be incremented (step 541) and, if α_{Test} is less than or equal to N-1 (step 531), then steps 530 may be repeated.

The estimation of the parameters accomplished in steps 530 also may be performed, for example, by decrementing α_{Test} from a high value to a low value, or by performing a random selection of α_{Test}. Under any of the approaches mentioned, parameters may or may not be estimated for each value of α_{Test}.

Following completion of the iterative process of steps 530, the estimated values of g_{max}, $\hat{\alpha}$, and $\hat{Y}_{ps}$ may be used to correct the offset of the data y_n (step 550). For example, using $\hat{\alpha}$ as the estimate of the transition point of the step function, the estimate $\hat{c}1$ may be expressed using the calculated values as

$$\hat{c}1 = \frac{1}{\hat{\alpha}} \hat{Y}_{ps}, \tag{1.24}$$

while $\hat{c}2$ may be expressed as

$$\hat{c}2 = \frac{1}{N - \hat{\alpha}} \left(Y_s - \hat{Y}_{ps} \right). \tag{1.25}$$

Optionally, where $\hat{c}1$ and $\hat{c}2$ as estimated above are equal or approximately equal (indicating that a step function may not be present), then both may be re-estimated as

$$\hat{c}1 = \hat{c}2 = \frac{1}{N} \left(Y_s \right). \tag{1.26}$$

Thereafter, to correct the offset of the received data y_n, the

estimated parameters may be used to subtract the step function from each data point as follows

$$y_n = \begin{cases} y_n - \hat{c}1, & 0 \le n < \hat{\alpha} \\ y_n - \hat{c}2, & \hat{\alpha} \le n < N. \end{cases} \qquad (1.27)$$

Following the correction of the offset, further estimation methods may be applied to the residual data (y_n minus the step function) in order to estimate the remaining unknown signal parameters θ.

Other implementations are within the scope of the following claims.